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ADAPTING SPACE VEHICLE SYSTEMS TO MEASUREMENT CONDITIONS

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A method is proposed for stabilizing the operation of a measurement system while adapting it to the on-board measurement conditions.

Key words: *space vehicle, independent functioning, virtual measuring instruments, adaption of on-board measurement systems.*

An analysis of promising technologies for managing space vehicles (SV) has shown that considerable value attaches to increasing the independent working time. For example, an increase to 30 days leads one to expect a reduction in the number of telemetry sessions by factors of 5–15, which in turn reduces the costs of providing SV functioning [1]. However, it is then necessary to transfer some of the functions from the ground control system to the SV, particularly monitoring the state and checking the correctness of the on-board equipment functioning. Such tasks are currently handled by means of a branched measuring system, which includes on-board telemetry systems, a network of ground telemetry systems, data-transmission systems, a telemetry information processing center, and groups for the analysis of SV control points. A key element is provided by the experts in the analysis groups, who monitor the state of the space vehicle by planning telemetry programs and analyzing the results.

However, for an independent SV, that element is partially ruled out from the control loop, and the main emphasis is placed on the on-board monitoring systems (OBMS). It is proposed that the analysis groups in the main will act when a nonstandard situation is encountered on the SV. In future, OBMS should possess a high level of artificial intelligence, to guarantee the monitoring of SV state with the required performance. Existing systems do not meet that requirement, so it is important to develop OBMS capable of partially replacing the intelligence of the analyst. The main attention should be given to methods implemented by the software in the on-board computer.

The monitoring includes accumulating and surveying a priori information on the object, with the derivation of measurement information, which is the most dynamic factor, followed by analysis and decision [2]. Therefore, transferring the monitoring task on the SV imposes tightened specifications for obtaining measurement information. Low-grade measurements lead to incorrect conclusions on the state, which in turn leads in the simplest case to additional access to the ground control and reduction in the independent working time, or in more complicated situations to complete loss of the object. The measurement data are obtained with the on-board measurement system OBMS. A feature of SV is the constant variability of the working conditions, which is reflected for the OBMS in changes in the setting under which the monitored parameters are measured. For example, there may be changes in temperature, pressure, or humidity within the SV, which produce additional errors of measurement, and in addition there is inevitable natural ageing (wear), which involves changes in characteristics of the entire system or failure in some elements, with the result that the measurement task cannot be performed by

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the method selected. The total number of monitored parameters on an SV may attain several thousand, and they include those of the circumstances on board: temperature, pressure, humidity, and so on.

It appears that the OBMS in a future system should have the capacity to eliminate these uncertainties by self-modification, i.e., adaptation. This can occur by changing the composition of the measured parameters or the methods of measurement, the number of measurements, the methods of processing the information, and so on. Particular interest for adaptive OBMS is constituted by specialized software for virtual measuring systems [3]. In practice, this is a package of applied programs of Lab VIEW type, which are parts of such systems (instruments). To use the properties of the software in virtual instruments, leads one to hope that existing OBMS will have the capacity for modification in accordance with changes in the measurement positions when changes are made in the SV software.

Adaptation should be controllable and not be chaotic; intelligent adaptive OBMS are required, whose functions should include adaptive control, which allows the software to avoid uncertainties [4]. It is therefore important to develop methods for realizing OBMS with adaptation to measurement setting conditions.

We consider such a system as a set of software and hardware realizing certain technologies for measuring the monitored parameters in order to handle the measurement tasks.

By measurement technology we mean a set of methods of obtaining and processing information, with presentation in the form required by the user. The measurement technology concept relates to an individual parameter, and the set of technologies forms a measurement program. In that case, the OBMS operation consists in performing that program. The measurement technologies are realized under dynamically varying conditions, which constitute a set of influencing factors.

Measurement technologies have a qualitative definiteness: informativeness, reliability, and promptness. We consider reliability as a property of measurement technology to provide the user with objective information. The reliability parameter is a probability measure characterizing the degree of confidence in the fact that the true value of the measured quantity and the result of measurement lie within a single uncertainty interval Δ :

$$P_c\{\Lambda \in [\Lambda^* - \Delta; \Lambda^* + \Delta]\} = a,$$

where P_c is the confidence probability, Λ the true value, Λ^* the measurement result, Δ the uncertainty interval, and $a \in [0; 1]$.

By informativeness is meant the property of the measurement technology to provide the user with the required quantity of information. The relevant parameter is the amount of information obtained by measurement with technology L_T :

$$J_{LT} = \ln(L/\Delta),$$

where L is the scale length of the measurement channel and Δ the measurement error.

The promptness of the measurement technology is considered as the length expressed in time units of the process for estimating the measurement results.

One provides the given quality in the measurement technologies, i.e., the required informativeness, reliability, and promptness when there are possible changes in the measurement conditions if the OBMS can be adapted. To do this, one needs an adaptation operator, which is implemented as an additional adaptation loop in the feedback, which uses deviations in the output signals from the required values to take decisions on controlling the system parameters. Major points are the definition of adaptation operator structure and functional laws.

The *formulation* of adaptation to changing measurement conditions in general appears as follows. Input data:

1) the functional model is a set of technologies for measurement L_T that display a set of control parameters Λ in the set of measurement result estimates of the values Λ^* under given measurement conditions $\{Q(t)\}$:

$$\{L_T\} : [\{\Lambda\} \rightarrow \{\Lambda^*\}; Q(t)];$$

2) the set of destabilizing factors $q_\lambda(t) \in \{Q\}$ and their functions of influence on the measurement results f_q : $q_\lambda(t) \rightarrow \Delta_q$;

3) the measurement equation for an individual parameter:

$$\Lambda^* = \Lambda \pm \Delta_\lambda, P_c,$$

where Δ_λ is the measurement error incorporating the basic and additional errors determined by the measurement system, $\Delta_\lambda = \Delta_\lambda^b + \Delta_q$;

4) the set $\{L_T\}$ of measurement technologies for the monitored parameters Λ , $L_{Ti} \subset \{L_T\}$, $i = \overline{1, m}$, where L_{Ti} is an individual technology; and

5) the structure of the measurement technology L_{Ti} :

$$L_T = \langle \Lambda, F, N, \tau, F_\lambda, F_{\lambda^*}, q^*, f_q \rangle,$$

where Λ are the measured quantities, F is the measured parameter transformation function, N the number of measurements in unit time, τ the measurement time, F_λ the methods of obtaining the measurement results, F_{λ^*} methods and means of processing the measurement results, q^* estimates of the individual unfavorable factors, and f_q the functions for the influence of the unfavorable factors on the measurement results.

The following are the parameters and quality criteria for handling the measurement task: $J_{LT} = f(L_T)$, $d_{LT} = f(L_T)$ informativeness and reliability in the measurement technology; $\tau_\Sigma = f(L_T)$ time consumed in handling the measurement task; $J_{LTi} \geq J_{\text{req}}$ for $d_{LTi} \geq d_{\text{req}}$; $\tau_\Sigma \leq \tau_{\text{req}}$ the quality criterion for the solving the measurement task; $\Delta J_{LTi} = J_{LTi} - J_{\text{req}}$ the discrepancy structure; and J_{req} , d_{req} , and τ_{req} are the required quality parameters.

It is required to synthesize the adaptation operator $G_A: \Delta J_{LTi} \rightarrow L_T^A$, providing for $\forall q_\lambda(t) \subset \{Q\}$ the obedience to the given criterion.

Solution. In general, adaptation involves defining a control algorithm for the measurements from estimates of the discrepancy, particularly determination of the set of control actions, which is dependent on the control object. In the present case, the control object is the operation of the OBMS, i.e., the measurement technologies for the individual parameters. The adaptation should occur at two levels: at the level of an individual technology $L_{Ti} \subset \{L_T\}$ and in the case of impossibility of meeting that criterion, then at the level of the measurement program. Then the set of control actions at the first level will be determined by the structure of the measurement technology and the control will consist in changing the structure parameters, while the set at the second level is the set of measurement technologies, and control in that case will consist in choosing a suitable technology, e.g., by simple scanning.

The adaptation operator G^A will be a compound one:

$$G^A = \{G_1^A, G_2^A\}, \text{ where } G_1^A: \Delta J_{LTi} \rightarrow L_{Ti}^A; G_2^A: \Delta J_{LTi} \rightarrow L_{Tj}^A,$$

with $i \neq j$.

Correspondingly, in the common loop one has two coupled adaptation loops at the first and second levels.

In general, there are three basic stages in the adaptation:

- 1) identifying discrepancies in the performance parameters;
- 2) choosing the control action; and
- 3) modifying the measurement program in accordance with the selected control.

Identifying the discrepancy involves determining the numerical value in the implementation of the selected measurement technology:

$$\Delta J_{LTi} = J_{LTi} - J_{\text{req}} = \ln(L/\Delta_\lambda) - \ln(L/\Delta_{\text{req}}) = \ln(\Delta_{\text{req}}/\Delta_\lambda),$$

where Δ_λ is the current error in measuring Λ derived in realizing technology L_{Ti} , and Δ_{req} is the required error of measurement to provide J_{req} .

The discrepancy is thus determined by the accuracy relation between the planned technology and the actual realization under particular measurement conditions. The expression shows what amount of information is obtained relative to the

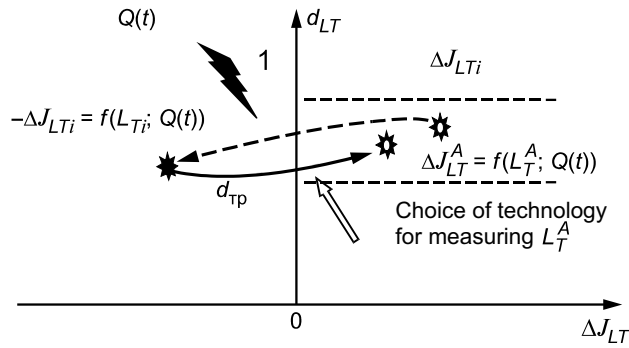


Fig. 1. Adaptation principle.

required value. If the error of the measurement result lies in the tolerance field, then the difference ΔJ_{LTi} is positive, and the measurement technology is informative. Otherwise, the difference will be negative and the results may be characterized as spurious (disinforming), and the entire negative region is a zone of elevated risk.

Figure 1 represents the adaptation of the OBMS to measurement conditions. The coordinate axes are the following parameters: the information discrepancy ΔJ_{LT} and the reliability d_{LT} . The dashed line shows the region of permissible values, which is specified in accordance with the measurement conditions as expressed by the performance criterion. If the performance parameter estimators appear in this region, it means that the measurement task has been performed.

The unfavorable factors increase Δ_q and correspondingly the resultant error. Then the value of the difference in informativeness from the required value is decreased:

$$\Delta J_{LTi} = \ln(\Delta_{\text{req}}/(\Delta_\lambda + \Delta_{\text{req}})).$$

A point may be reached where the resultant error $\Delta_\lambda = \Delta_\lambda + \Delta_q$ exceeds the permissible value $\Delta_{\text{req}} < \Delta_\lambda$; then the difference becomes negative:

$$-\Delta J_{LTi} = f(L_{Ti}; Q(t)).$$

Then the minus sign denotes reduction in measurement quality and is a signal for performing the control of the OBMS.

An essential point is determining the value and structure of the current error Δ_λ and in particular the presence of an additional error Δ_q and how it occurs. For example, a systematic error displaces the measurement result relative to the true value, while a random error smears out the possible value range. The current error may be determined by certain methods [5] with three instruments, Wald's method, group evaluation, statistical processing, with built-in sensors, and by measurement of calibrated values.

Then identifying the informativeness discrepancy amounts to identifying the structure of the current measurement error Δ_λ , which determines the subsequent control choice.

The next step is to choose the control action. At the first adaptation level, it is determined by the structure of the current measurement error. If the systematic component $\Lambda_\lambda^{\text{sys}}$ predominates in the structure, the choice of controls includes excluding the following error forms:

- a constant systematic error, where the commonest practices are methods of introducing corrections, substitution, and error sign compensation;
- a variable systematic error, particularly one varying in a complicated way, for which one uses negative feedback methods, auxiliary measurements, standard measures, test measures, and so on; and
- a variable periodic error handled by performing measurements in those time intervals when it is zero.

If the random component Λ_λ^r predominates, one increases the number of measurements on the basis that

$$\sigma_{\bar{\lambda}} = \sigma_\lambda / \sqrt{N}$$

until the interval of random error becomes comparable with the residual systematic error or further increase in the number of measurements becomes undesirable.

If on the other hand at the first level of adaptation one cannot resolve the task with the required performance, then the control at the second level involves surveying the set of measurement technologies $\{L_T\}$.

For example, for the first adaptation level, the modification is made in accordance with the rule:

IF $\Delta J_{L_{Ti}} \geq 0$ for $d_{L_{Ti}+r} \geq d_{req}$; $\tau_\Sigma \leq \tau_{req}$, THEN L_{Ti} ,

ELSE modification L_{Ti} in accordance with the error structure;

IF Δ_λ^{sys} , THEN correct the measurement result and estimate the interval for the random error Δ_λ^r OR the following condition:

IF Λ_λ^r THEN increase $N = (\sigma_\lambda / \sigma_{\bar{\lambda}_{req}})^2$ while $\Delta_\lambda^r > \Delta_\lambda^{sys}$.

Then we get a new measurement technology structure differing from the initial one:

$$L_{Ti}^A = \langle \Lambda_i'^*, F', N', \tau', F_\lambda', F_\lambda'^*, q'^*, f_q' \rangle,$$

For the second adaptation level:

IF $\Delta J_{L_{Ti}}^A \geq 0$ for $d_{L_{Ti}} \geq d_{req}$; $\tau_\Sigma \leq \tau_{req}$, THEN L_{Ti}^A ,

ELSE survey the set $\{L_T\}$ and choose L_{Tj} or change the measurement program.

As a result, the OBMS realizes a new measurement program L_{Tj} differing from the basic L_{Ti} :

$$L_{Tj} = \langle \Lambda_j'^*, F_j', N_j', \tau_j', F_{j\lambda}', F_{j\lambda}'^*, q_j'^*, f_{jq}' \rangle.$$

Figure 2 shows the adaptation algorithm.

The next adaptation step is to modify the OBMS structure in the program environment in accordance with the selected control. However, the cycle involving solving the adaptation is not completed at this point, and on the basis of the structural changes, the system performs a repeated monitoring loop for the solution quality in the measurement task. From its results in accordance with the established rules, it takes a decision: measurement of the monitored parameters, passage to the second adaptation or training the system, where the main feature is the search for and use of positive controls involving additional information.

Example. Consider adapting the measurement procedure on monitoring the electrical power supply (EPS) when the measurement conditions change. A major characteristic of the EPS is the electrical energy reserve at a certain instant, which in turn is dependent on the initial capacity of the primary sources, the composition of the users, and their working time program, together with the energy consumption of instruments and SV systems in various modes (standby, working), the charging-discharging characteristics and the power of the energy sources as a function of working time. An error in monitoring the discharge of the EPS may lead to loss of the SV.

Let the measurement task be set as follows for monitoring the power parameter [3]:

$$\Lambda_p^* = L_T \{ \Lambda_p, (\Delta_{preq} = \pm 0.5 \text{ VA}; d_{L_{preq}} = 0.9; \tau_{req} = 1 \text{ sec}), \Delta J_{LT} > 0; d_{LT} > d_{req}; \tau_\Sigma < \tau_{req} \},$$

where L_T is the measurement technology represented by the model

$$L_T = \langle \Lambda_u; N_u = 1; \tau_u = 0.1 \text{ sec}; \Lambda_i; N_i = 1; \tau_i = 0.1 \text{ sec}; P = UI; \tau_p = 0.01 \text{ sec} \rangle.$$

Here Λ_u and Λ_i are the measured physical quantities (voltage and current), N_u and N_i are the numbers of measurements, τ_u and τ_i are the times for one measurement for the corresponding quantity, P the measurement method, and τ_p the calculation time.

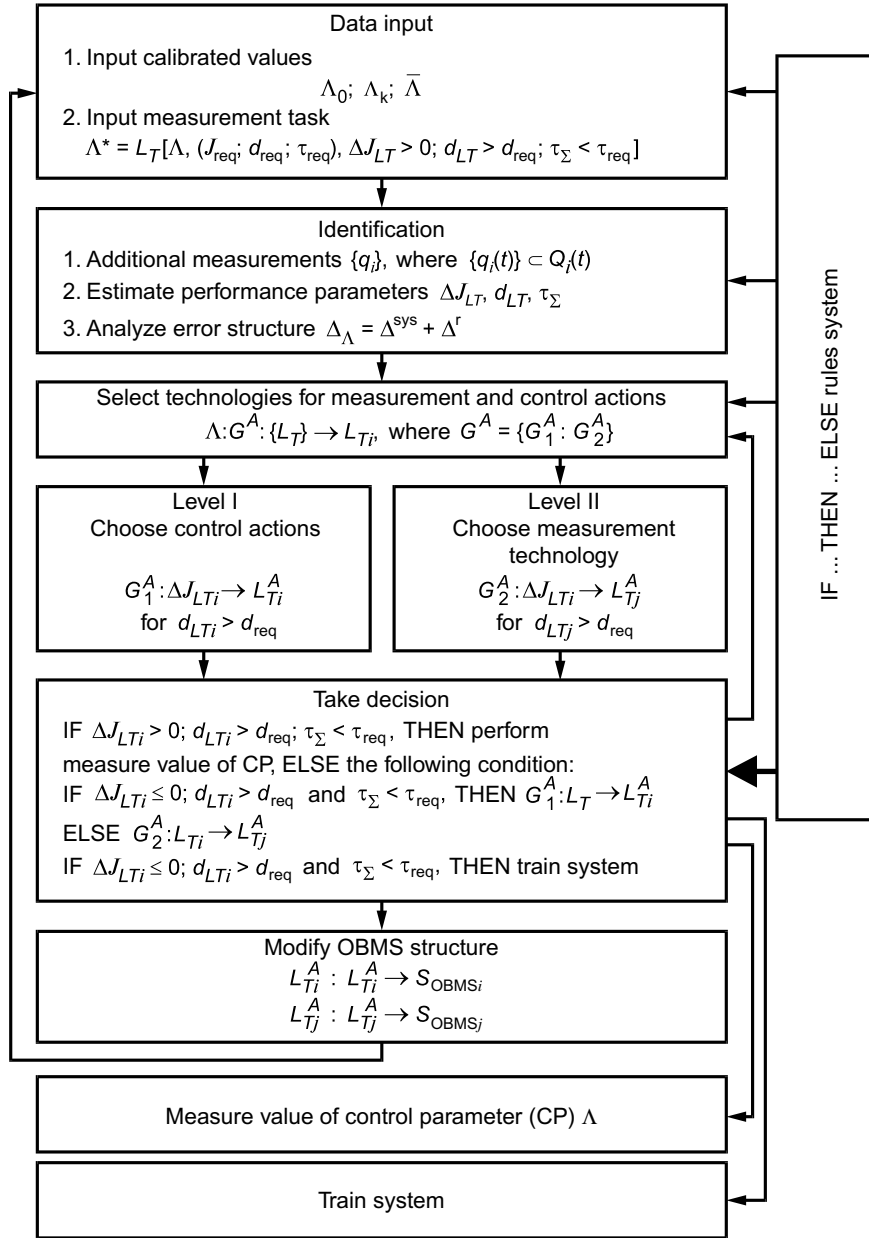


Fig. 2. Algorithm for additional control loop for on-board space vehicle measurement systems.

When a technology is realized at time t_k , it is expected that the power estimate Λ_p^* will be made with an error $\Delta_p = \pm 0.5$ VA and with confidence probability $P_c = 0.9$.

To calculate the uncertainty interval [6] $\Delta_p = (|\Delta_p^{\text{sys}}| + \Delta_p^r)$, we introduce the following assumptions about the measurement channels:

- voltage: standard deviation of observational results $\sigma_u = 0.14$ V, which corresponds to $\delta_u = 1\%$, the basic error under normal conditions;
- current: standard deviation of observation result $\sigma_i = 0.005$ A, which corresponds to $\delta_i = 1\%$, the basic error under normal conditions.

We assume that in the measurements and processing of these data we obtain an error $\Delta_p^{\text{sys}} \ll \Delta_p^r$ and it may be neglected. In that case, the error will be solely of random character (Fig. 3). There are various kinds of influencing factors, so we assume that they have a gaussian distribution, and to get an estimate of the entropy interval of uncertainty we use

$$\Delta_p = K_e \sigma_{p\Sigma} = 2.066 \cdot 0.145 = \pm 0.3 \text{ VA};$$

$$P_c = 0.899 + \chi^2/5.5 = 0.899 + 0.57^2/5.5 = 0.96,$$

where Δ_p and P_c are the error and confidence probability found by experience from a series of observations (e.g., for $N = 10$) by the entropy method; K_e is the entropy coefficient, which is dependent on the form of the distribution, where $K_e \in [1.11; 2.066]$; $\sigma_{p\Sigma}$ is the total standard deviation in the observation result; and χ represents the corresponding distribution, $\chi \in [0; 1]$ [6].

We use the algorithm in the periodic estimation of the discrepancy, which consists in estimating the performance parameter of the measurement technology:

- informativeness discrepancy $\Delta J_{LT} = \ln(0.5/0.3) = 0.5$ nit;
- reliability of measurement result $d_{LT} = 0.96$; and
- time needed to solve measurement problem $\tau_\Sigma = 0.11$ sec.

These estimates correspond to the performance criterion in solving the measurement task, so the technology is informative (Fig. 4).

For example, let the temperature within the SV at a certain instant t_k rise to $T = 60^\circ\text{C}$, and against that background, noise occurs with a gaussian distribution, whose power may attain 0.6% of the value for a parameter (e.g., the standard deviation in the observational result for the voltage $\sigma_{u\text{ad}} = 0.22$ V, current $\sigma_{i\text{ad}} = 0.002$ A). We assume that we know the influence functions for the temperature T in the measurement channel and correspondingly those on the measurement results for the voltage $\Delta_{uT}^{\text{sys}} = 0.02(T - T_0)$ and current $\Delta_{iT}^{\text{sys}} = 0.001(T - T_0)$, where $T_0 = 20 \pm 5^\circ\text{C}$ is the initial value of the temperature, which corresponds to normal conditions, and T is the temperature at the time of measurement. The error in determining the temperature is considered as slight and will be neglected. Then under these conditions we obtain a certain value for the power Λ_p^* (Fig. 3), e.g., for $U_{\text{nom}} = 30$ V; $I_{\text{nom}} = 0.5$ A; $P_{\text{nom}} = 15$ VA:

- the systematic error for the voltage is $\Delta_{uT}^{\text{sys}} = 0.02(60 - 25) = +0.7$ V; $U^* = 30.7$ V, while for the current it is $\Delta_{iT}^{\text{sys}} = 0.001(60 - 25) = +0.04$ A; $I^* = 0.54$ A, and for the power it is $\Delta_p^{\text{sys}} = +1.66$ VA; $P^* = 16.6$ VA;
- the random error for the voltage is $\Delta_u^r = K_e \sigma_{u\Sigma}$, where $\sigma_{u\Sigma} = (\sigma_u^2 + \sigma_{u\text{add}}^2)^{1/2} = [(0.14)^2 + (0.22)^2]^{1/2} = 0.26$ V, $\Delta_u^r = 0.26 \cdot 2.066 = 0.54$ V, and analogously for the current $\sigma_{i\Sigma} = [(0.002)^2 + (0.001)^2]^{1/2} = 0.002$ A, $\Delta_i^r = 0.005$ A;
- the interval for the random error of the power $\Delta_p^r = \pm 0.54$ VA, $P_c = 0.96$; and
- the uncertainty interval for the power measurement result is $\Delta_p = |1.66| \pm 0.54 = 2.2$ VA, $P_c = 0.96$ (Fig. 3).

We identify the information discrepancy on the basis of the change in measurement conditions, and then:

- the informativeness discrepancy $\Delta J_{LT} = \ln(0.5/0.54) = -1.5$ nit;
- reliability of measurement result $d_{LT} = 0.96$; and
- time to resolve measurement task $\tau_\Sigma = 0.11$ sec, measurement.

These parameters differ from the previous ones and do not correspond to the performance criterion in the measurement task, i.e., the measurement technology under these conditions is not informative (Fig. 4).

Consequently, the next adaptation stage is to choose control actions at adaptation level I (Fig. 3):

- correct the measurement results (eliminate the systematic error component by the control actions);
- choose the number of measurements.

For example, when one uses additional measurements, the systematic error is eliminated by correction calculated from the influence function and the estimation (measurement result) of the influencing factor $T = 60^\circ\text{C}$, after which there remains the random component of the uncertainty interval (Fig. 3) $\Delta_p^r = \pm 0.54$ VA, $P_c = 0.96$, and correspondingly the estimates for the performance parameters are $\Delta J_{LT} = \ln(0.5/(0.54)) = 0.07$ nit; $d_{LT} = 0.96$; $\tau_\Sigma = 0.33$ sec.

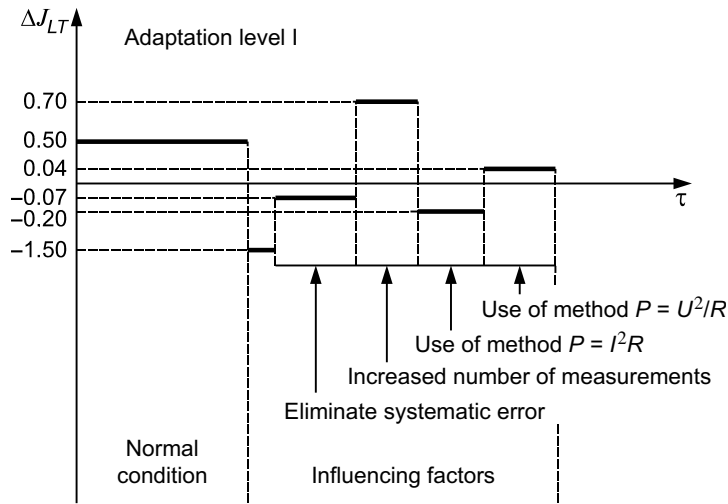


Fig. 4. Example of adaptation loop functioning.

Let the measurement technology for the first method be represented as

$$L_T = \langle \Lambda_u; N_u = 1; \tau_m = 0.1 \text{ sec}; \Lambda_r; N_r = 1; \tau_r = 0.1 \text{ sec}; P = U^2/R; \\ \tau_p = 0.03 \text{ sec}; \Lambda_T; \tau_T = 0.2 \text{ sec}; \Delta_{uT}^{\text{sys}} = f_q(T), \tau_p = 0.01 \text{ sec} \rangle.$$

We calculate the error in the measurement result with allowance for the weights of the arguments in the function and the correlations. We assume that the systematic error in the measurement channel for the voltage is eliminated and that the further processing is represented by corrected measurement results. Then the error interval for the voltage is $\Delta_u^r = 0.26 \cdot 2.066 = 0.54 \text{ V}$, where $\sigma_{u\Sigma} = 0.26 \text{ V}$, in accordance with the above calculations; the error interval for the resistance is $\Delta_r = \pm 0.6 \Omega$, where $\sigma_r = 0.29 \Omega$; and the error interval for the result of the power measurement is $\Delta_p = 2.066 \cdot 0.75 = 1.55 \text{ VA}$, $P_c = 0.96$, where $\sigma_{p\Sigma} = 2\sigma_{u\Sigma} - \sigma_r = 0.23 \text{ V}$; $\Delta_p^r = \pm 0.48 \text{ VA}$.

In the discrepancy identification, we get

$$\Delta J_{LT} = \ln(0.5/0.48) = 0.04 \text{ nit}; d_{LT} = 0.96; \tau_\Sigma = 0.44 \text{ sec}.$$

The $P = U^2/R$ method solves the measurement task with the required performance (Fig. 4), but there is a loss of promptness by comparison with the basic measurement technology.

Similarly, we analyze the measurement technology by the use of the second method:

$$L_T = \langle \Lambda_i; N_i = 1; \tau_i = 0.1 \text{ sec}; \Lambda_r; N_r = 1; \tau_r = 0.1 \text{ sec}; P = I^2R; \\ \tau_p = 0.01 \text{ sec}; \Lambda_T; \tau_T = 0.2 \text{ sec}; \Delta_{iT}^{\text{sys}} = f_q(T), \tau_p = 0.01 \text{ sec} \rangle.$$

The calculations give the uncertainty interval for the power measurement result as $\Delta_p = 2.066 \cdot 0.29 = 0.59 \text{ VA}$, $P_c = 0.96$, where $\sigma_{p\Sigma} = 2\sigma_{i\Sigma} + \sigma_r = 2 \cdot 0.005 + 0.29 = 0.294 \approx 0.29 \text{ VA}$, and the performance parameters as

$$\Delta J_{LT} = \ln(0.5/0.59) = -0.2 \text{ nit}; d_{LT} = 0.96; \tau_\Sigma = 0.44 \text{ sec}.$$

These data imply that the $P = I^2R$ method does not provide the required performance, but the most informative technology is the one that includes the $P = U^2/R$ method (Fig. 4), but its use in the present case is undesirable because of increase in the measurement time.

If one cannot handle the adaptation by these methods, one modifies the measurement program (level II adaptation) at the level of the monitoring task. For example, the parameter is completely eliminated from the estimation program for the power supply system characteristics, and other methods are used to solve the problem.

In conclusion, we note that the proposed adaptation algorithm can be quite simply implemented on the basis of the latest information technologies that employ the conception of virtual instruments. When one uses software for virtual meters (type Lab VIEW and so on), the elements of the measurement technology are represented as separate independent software modules linked by the address scheme into a program environment for a feature classification field. In that case, the measurement technologies are specified by the addresses of the element fields. The adaptation loop functioning on the above algorithm in accordance with the chosen technology calls up the necessary elements and provides links between them.

This adaptation algorithm provides stable solution to measurements of monitored parameters on board future SV under various measurement conditions and thus improves the level of independence of the functioning.

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